Recovery of Cities after Disasters and Pandemics via Mobility Data Analytics

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Distinguished Seminar

Asian Development Bank Institute

PURDUE UNIVERSITY

Urban Mobility, Networks and Intelligence Lab

15 Year Experience working on Disaster Research

- Survey Data: **Hurricanes** Katrina, Ivan, Rita, Sandy, Harvey Maria
- Various Earthquakes and Tsunamis
- Behavioral Intention Surveys – Understanding decision making of households in disasters (pre and post)
- Social Network Surveys – Understanding the structure of social nets and their influence on decision making in disaster response and recovery
- Advantages
  - Representative Sample
  - Socio-Demographic Information is available
- Disadvantages
  - Lacks spatio-temporal granularity
  - Longitudinal data is unavailable
  - Sample size is limited

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- Inequality of recovery outcomes
- Systems dynamics model
- Future work: pandemics x disasters

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Disaster resilience: a global challenge

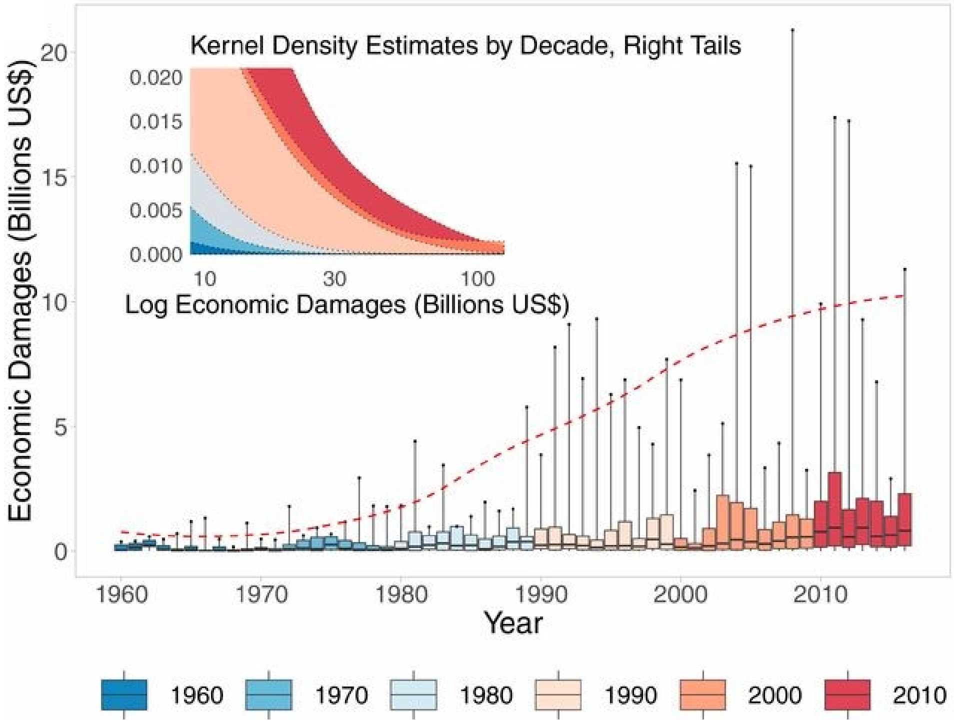
- $2.9T economic loss in 20 years globally, and increasing.
  - Especially the extreme (“long tailed”) events.
  - Due to climate change and rapid urbanization.
    - 54% population live in urban areas (2016)
    - Projected increase to 68% by 2050.

- Improving the ***resilience of cities to disasters*** is one of the key goals for development agencies.

UNDRR
UN Office for Disaster Risk Reduction

THE WORLD BANK

SUSTAINABLE DEVELOPMENT GOALS



[Coronese et al., 2019]

Opportunity: Large scale mobility data

- GPS/call detail record data collected from mobile phones via apps
- Key features:
    - 1~5% sample of the total population.
    - 50~100 points per user each day.
        - Can estimate staypoints but not routes
    - Do not contain demographic information.
        - Estimate using census data (e.g. Yabe and Ukkusuri, 2020)

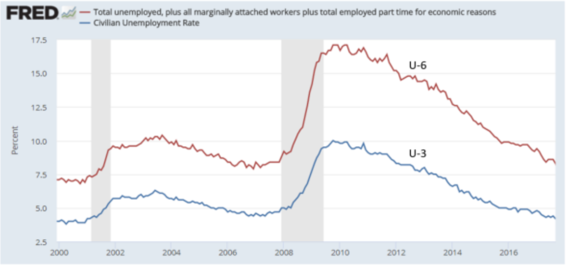
- Mobile phone location data contain bias in socio-economic population groups.
    - Accessibility to technology, age-groups, wealth, etc.
    - However, macroscopic analysis usually yield robust results (e.g. urban population density estimations), as shown in several previous studies (Deville et al., 2014; Blondel et al., 2015).

Data Representativeness

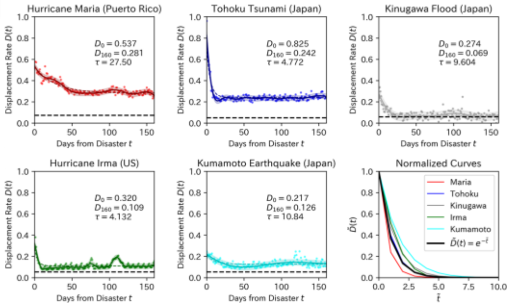
- Mobile phone data may contain bias particularly in low income nations
- Studies have shown (Wesolowski, 2013) that in countries such as Rwanda and Kenya are not representative of the entire population – bias towards males, educated groups and large households
- Mobile phone location data contain bias in socio-economic population groups.
  - Accessibility to technology, age-groups, wealth, etc.
  - However, macroscopic analysis usually yield robust results (e.g. urban population density estimations), as shown in several previous studies (Deville et al., 2014; Blondel et al., 2015).
- Bias in developed countries is not established
- Bias correction techniques can be used – Raking, Weighting methods

How can we use such data?

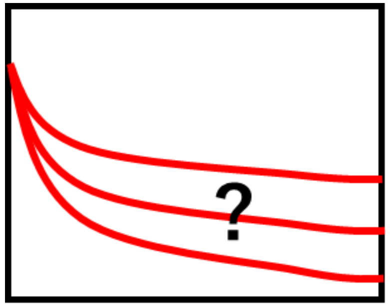
1. **Evaluation** of ongoing infrastructure related investment decisions.
   - How beneficial were the investments on highway corridor X?
2. **Prediction** of recovery outcomes of communities after future disasters.
   - How will population recover in city X after disaster Y?
   - What would be the demand for public utilities in city X after 2 weeks from disaster?
3. **Re-design** of connectivity between cities to prevent isolation and foster recovery through road investments.
   - How would the recovery of city X improve by strengthening the connection with city Y?



Monitoring economic resilience around highway corridors

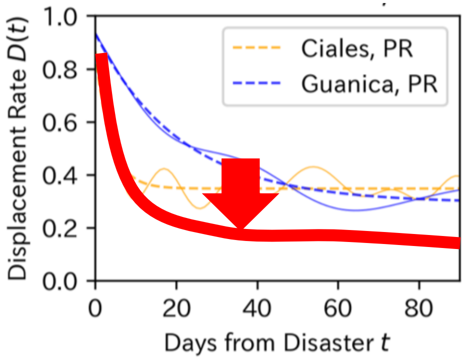


Prior observations



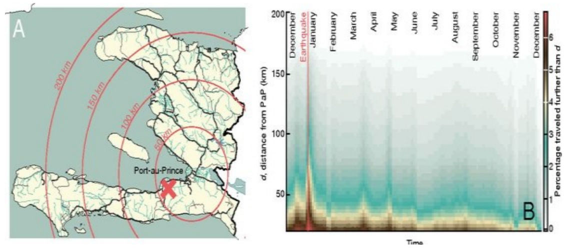
Predictions

Construction of road

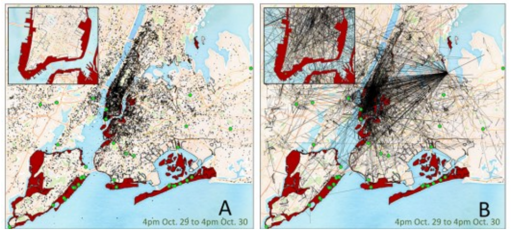


Challenge: Lack of data-driven models for recovery

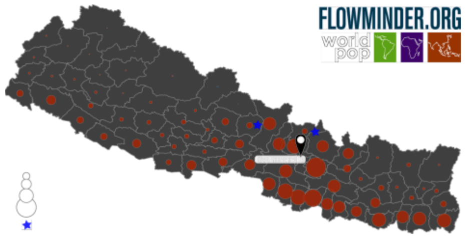
- Studies using mobility data for post-disaster displacement analysis
  - ✓ Mobile phone call detail record data
    - Haiti Earthquake (Lu et al., 2012)
    - Nepal Earthquake (Wilson et al., 2016)
  - ✓ Mobile phone GPS location data
    - Kumamoto Earthquake (Yabe et al., 2019)
  - ✓ Twitter geo-tagged data
    - Hurricane Sandy (Wang et al., 2014)
- Focus on initial short term movement (~1 month)



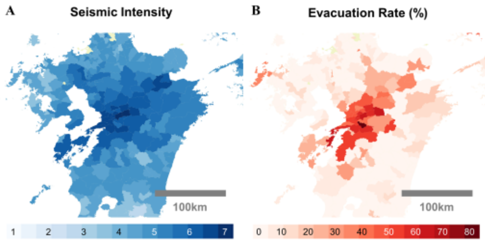
Haiti Earthquake (Lu et al., 2012)



Hurricane Sandy, Twitter (Wang et al., 2014)



Nepal Earthquake (Wilson et al., 2016)



Kumamoto Earthquake (Yabe et al., 2019)

Lack of methods to utilize large-scale mobility data for modeling long-term post-disaster population dynamics!

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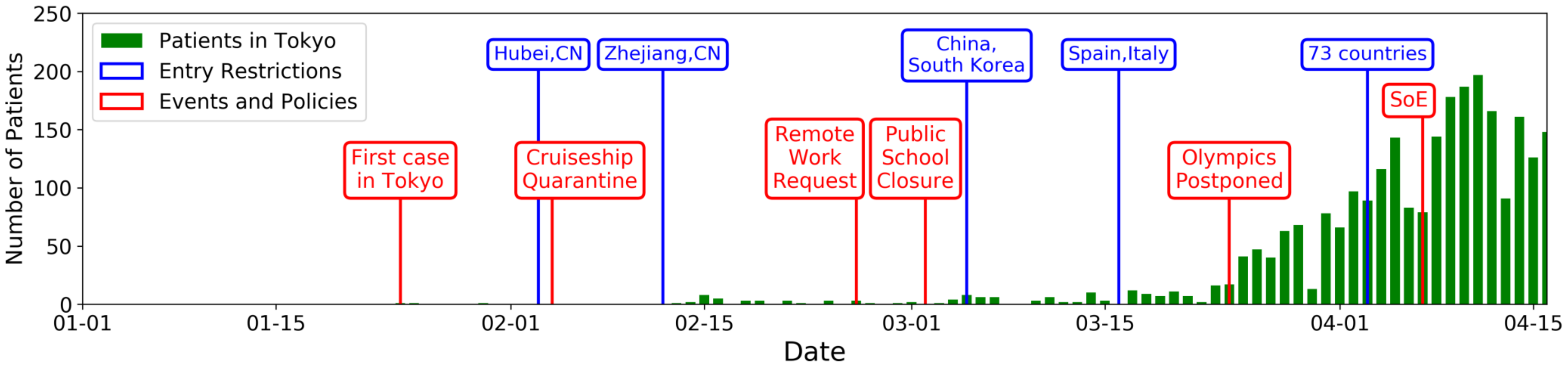
Only non-compulsory measures were taken in Japan



- Japan = a unique study!
  - Only non-compulsory non-pharmaceutical interventions (no lockdowns)
  - Small count of patients and deaths despite proximity to origin of spread.

→ **Can we understand why through mobility data analytics?**

Non-Compulsory Measures Sufficiently Reduced Human Mobility in Japan during the COVID-19 Epidemic. Yabe et al. (2020) https://arxiv.org/abs/2005.09423

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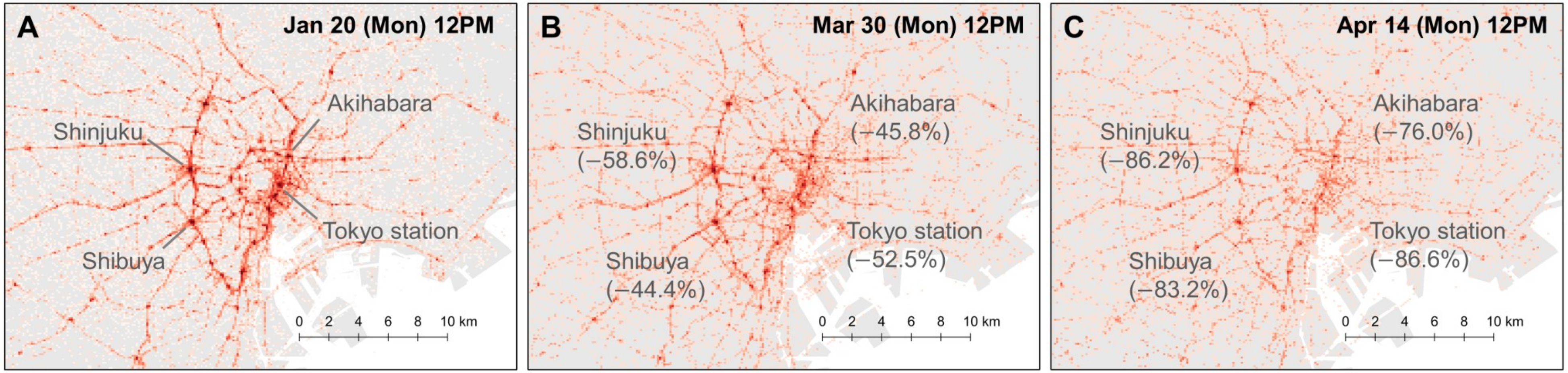

- Mobile phone data (Yahoo Japan) tells us that major stations had 80% reduction of visitors compared to typical periods.

Some questions:

- How did the people's contact patterns change?
- If so, how did that affect the transmissibility of COVID-19 in Tokyo?

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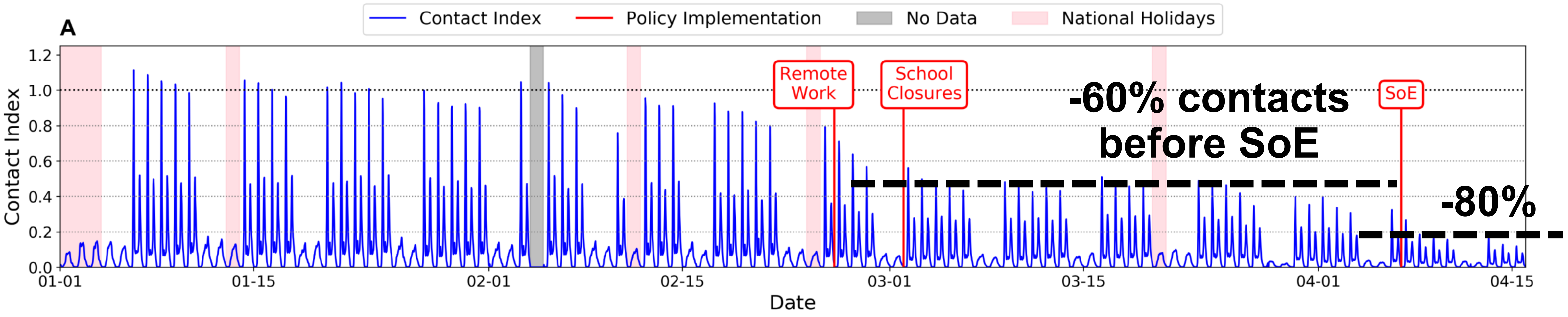
Decrease in social contacts before/after SoE



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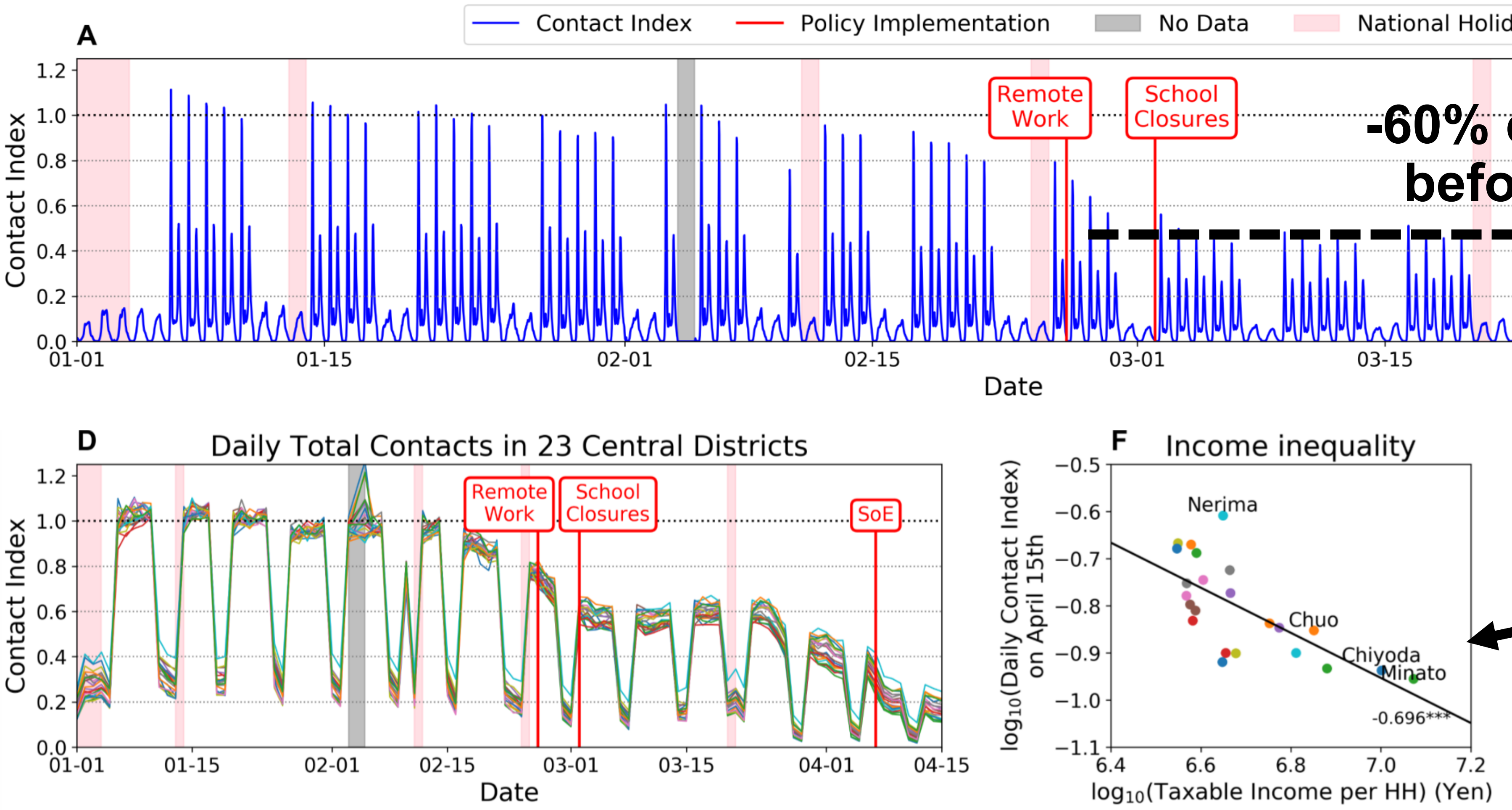
Income inequality in contact reduction



Income inequality: Richer reduced more contacts

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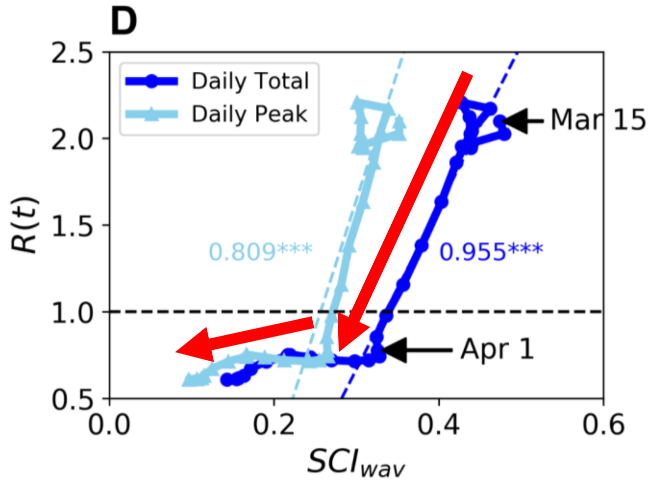
Strong correlation between mobility and $R(t)$



Reduction of social contacts correlate with lower $R(t)$, but only up to a certain level...

→ How much is optimal contact reduction?

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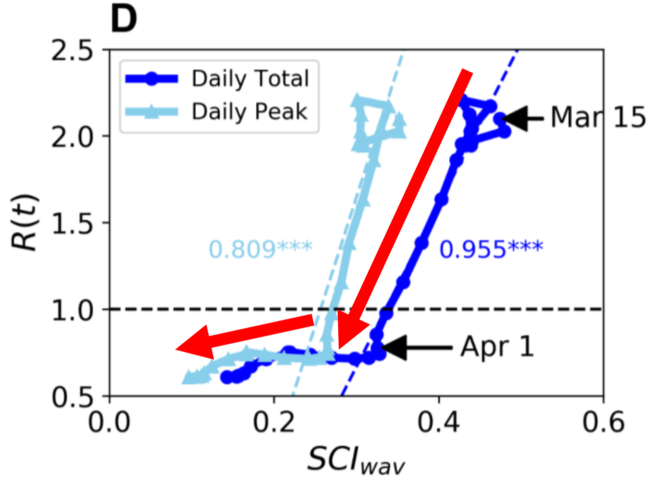

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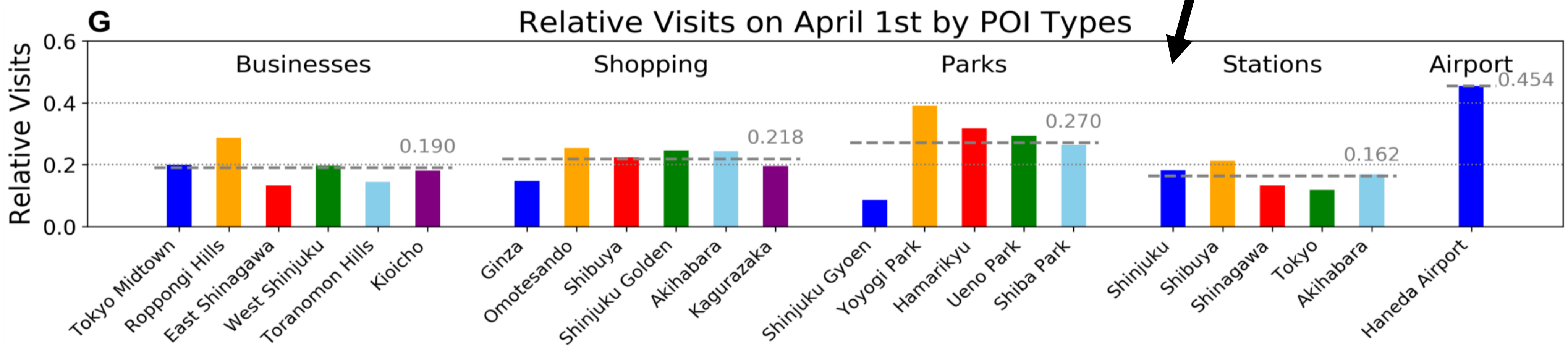
How much is "0.65" social contact reduction?



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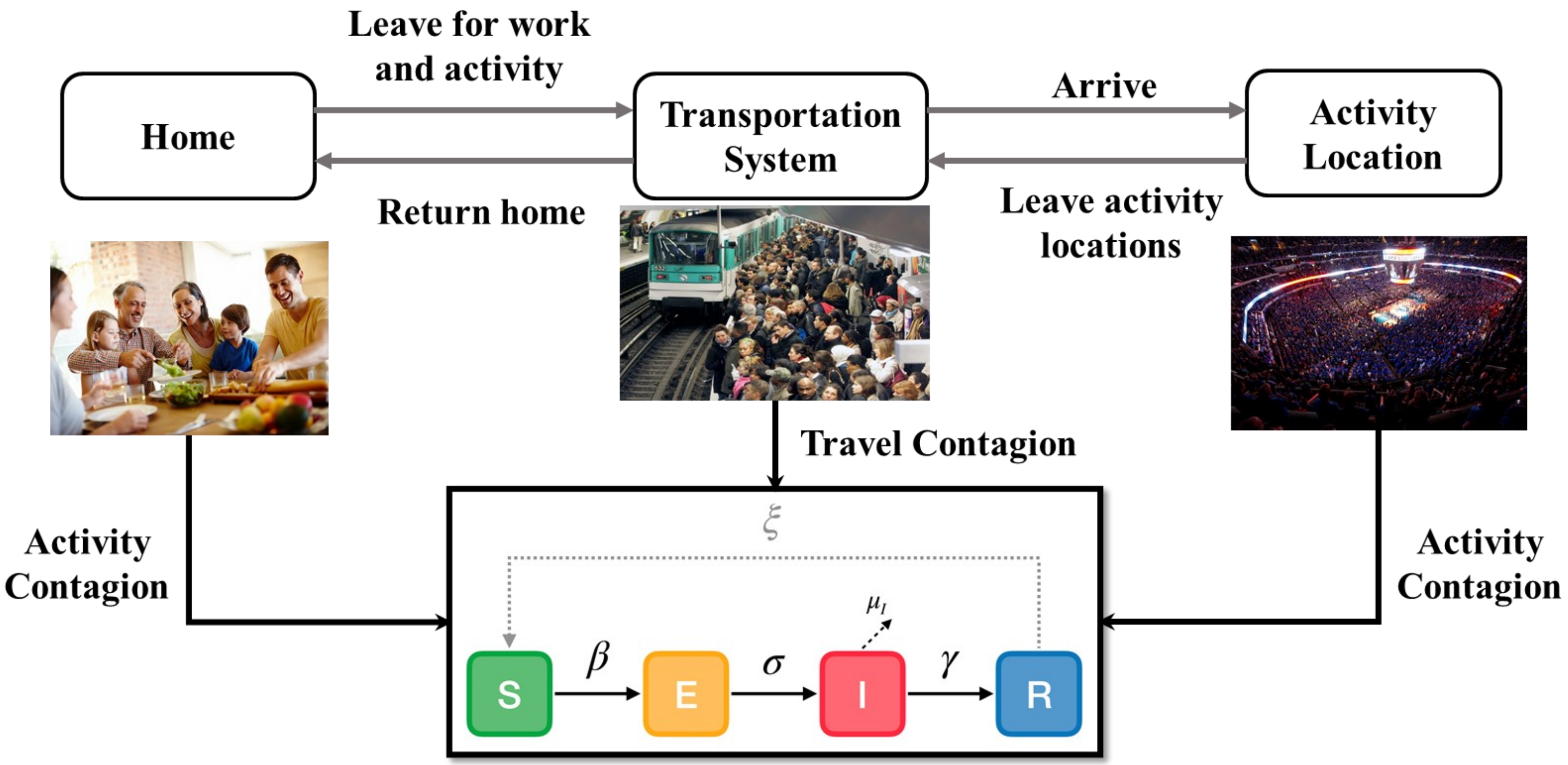
Trans-SEIR model: overview

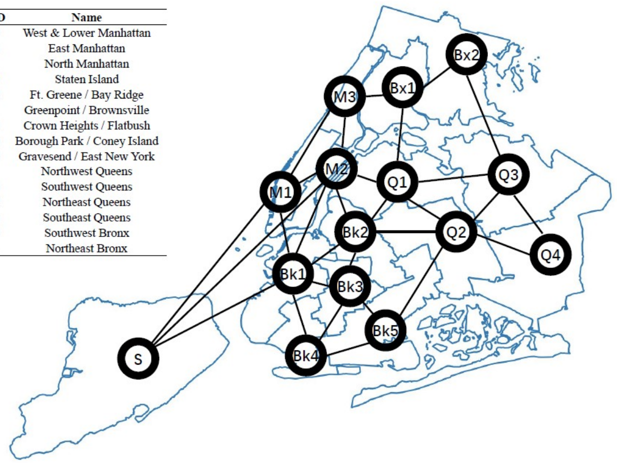
- Objective: Understand the role of urban transportation systems in the spread of infectious diseases in urban areas
  - Spatial movements of urban commuters / Various type of contagion events
  - Can we control the transportation system to stop the spread of infectious diseases?

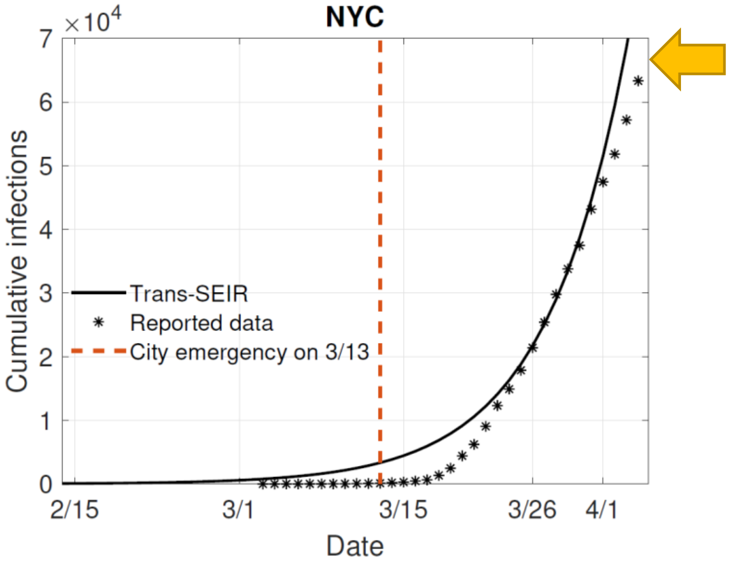


Trans-SEIR model: NYC case study

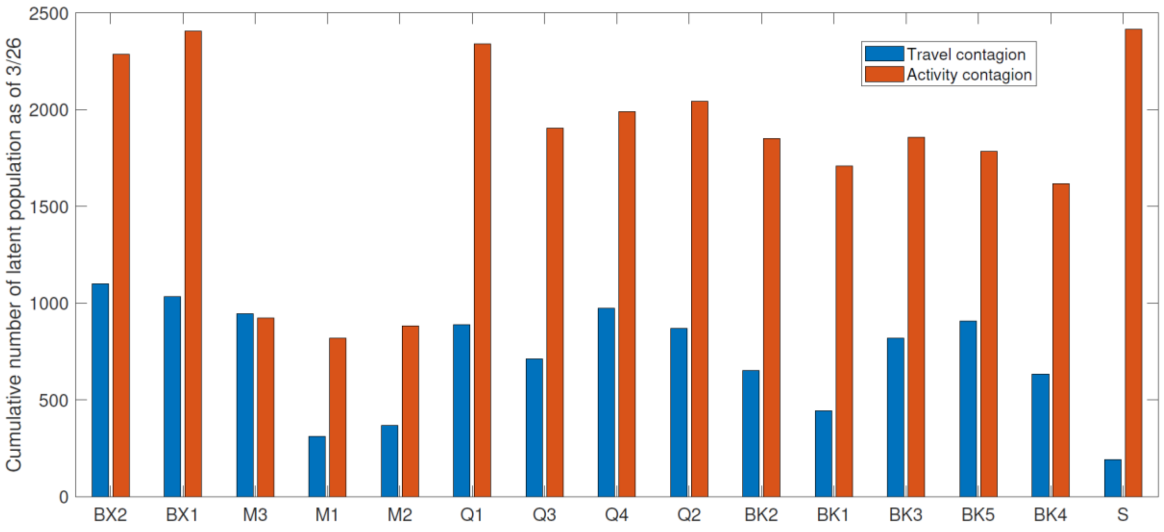
- COVID-19 data and NYC commuting data
- Estimated R_0: 3.295
- Travel contagion: 28.6% of total cases during early outbreak, but varies locally due to different transit usage patterns
- West & Lower Manhattan is the intermediate point: people get infected here, then bring the disease back for local infections

Node	Zone ID	Name
M1	36102	West & Lower Manhattan
M2	36103	East Manhattan
M3	36101	North Manhattan
S	36130	Staten Island
BK1	36122	Ft. Greene / Bay Ridge
BK2	36121	Greenpoint / Brownsville
BK3	36123	Crown Heights / Flatbush
BK4	36125	Borough Park / Coney Island
BK5	36124	Gravesend / East New York
Q1	36111	Northwest Queens
Q2	36114	Southwest Queens
Q3	36112	Northeast Queens
Q4	36113	Southeast Queens
BX1	36092	Southwest Bronx
BX2	36091	Northeast Bronx





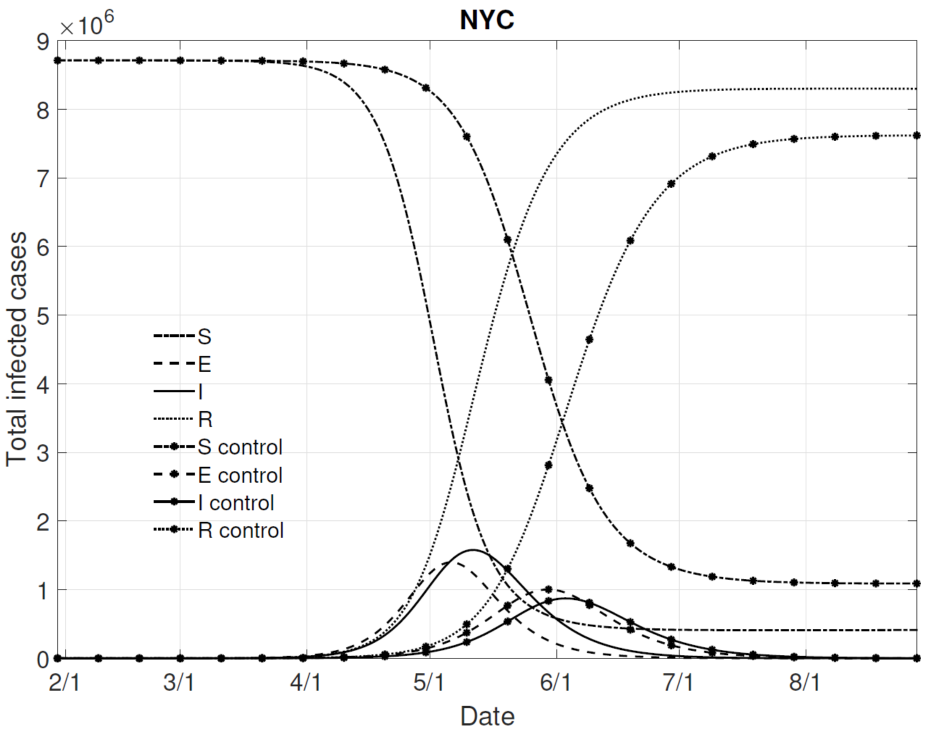
Trans-SEIR model results vs reported data (Divert approx. 2.5 weeks after the announcement of city emergency)



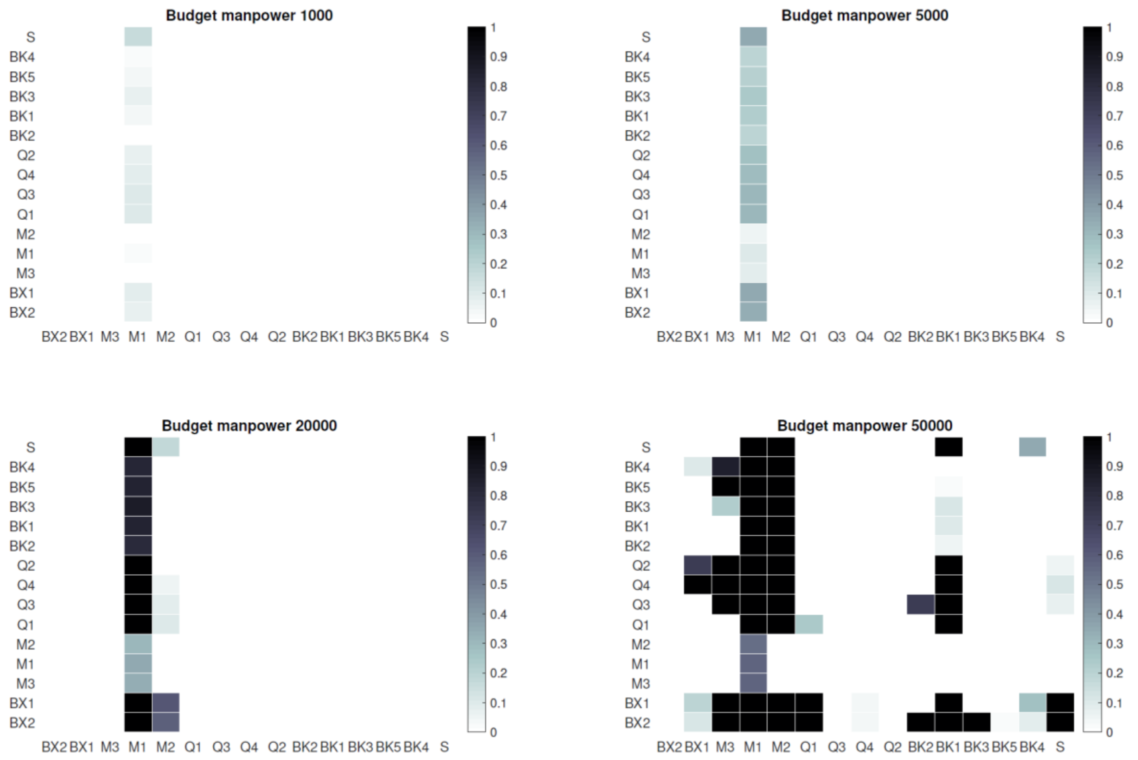
Travel and activity contagions at different locations in NYC as of March 26, 2020

Trans-SEIR model: NYC case study

- If preventative / early entrance control was placed in NYC:
  - May save 700k commuters from being infected, and delay the peak by 25 days



Potential disease dynamics with and without transit entrance control (Budget of 2,000, No other intervenes)



The optimal distribution of resources under various budget level

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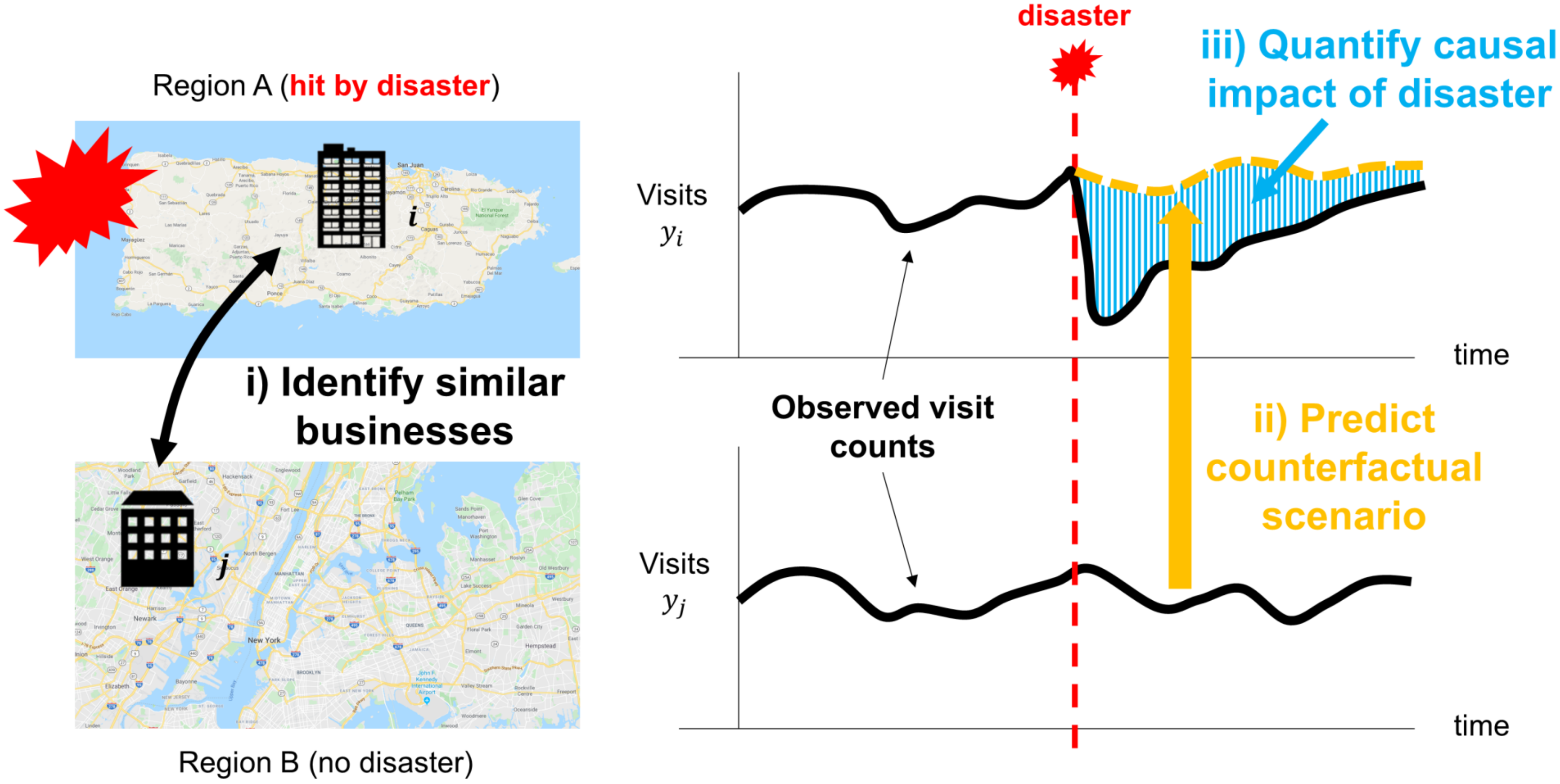
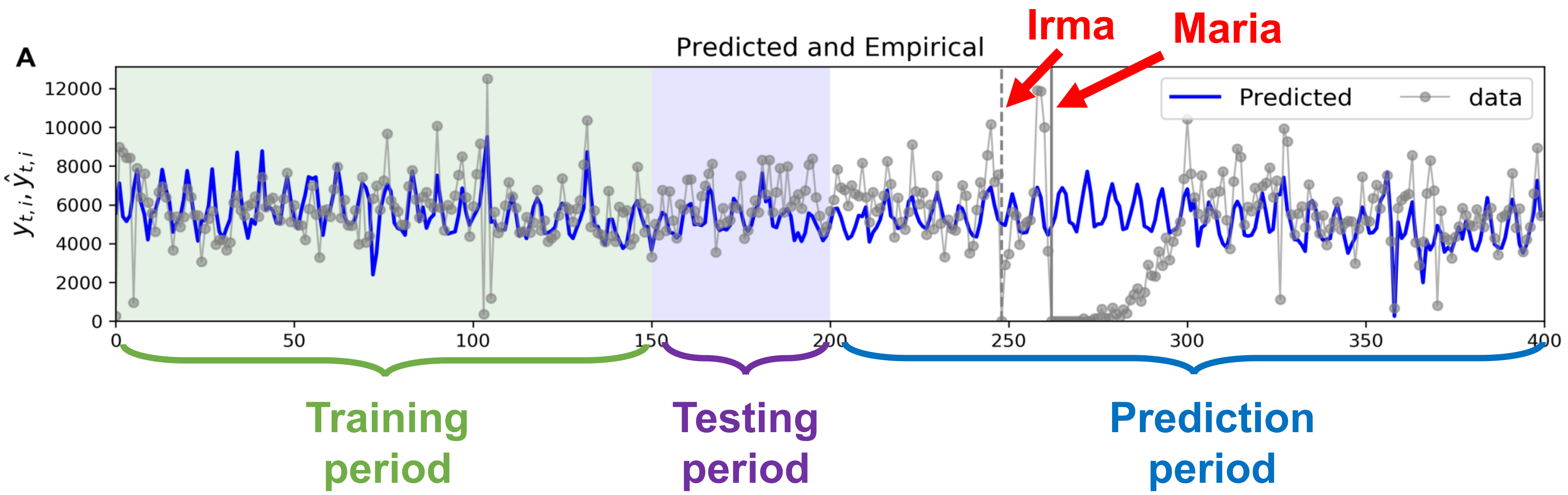
Economic impacts of disasters via mobility analytics



Quantifying the Economic Impact of Extreme Shocks on Businesses using Human Mobility Data: a Bayesian Causal Inference Approach. Yabe et al. (2020) https://arxiv.org/abs/2004.11121

Estimation results for a single business case:

- An example of a Walmart in San Juan, Puerto Rico



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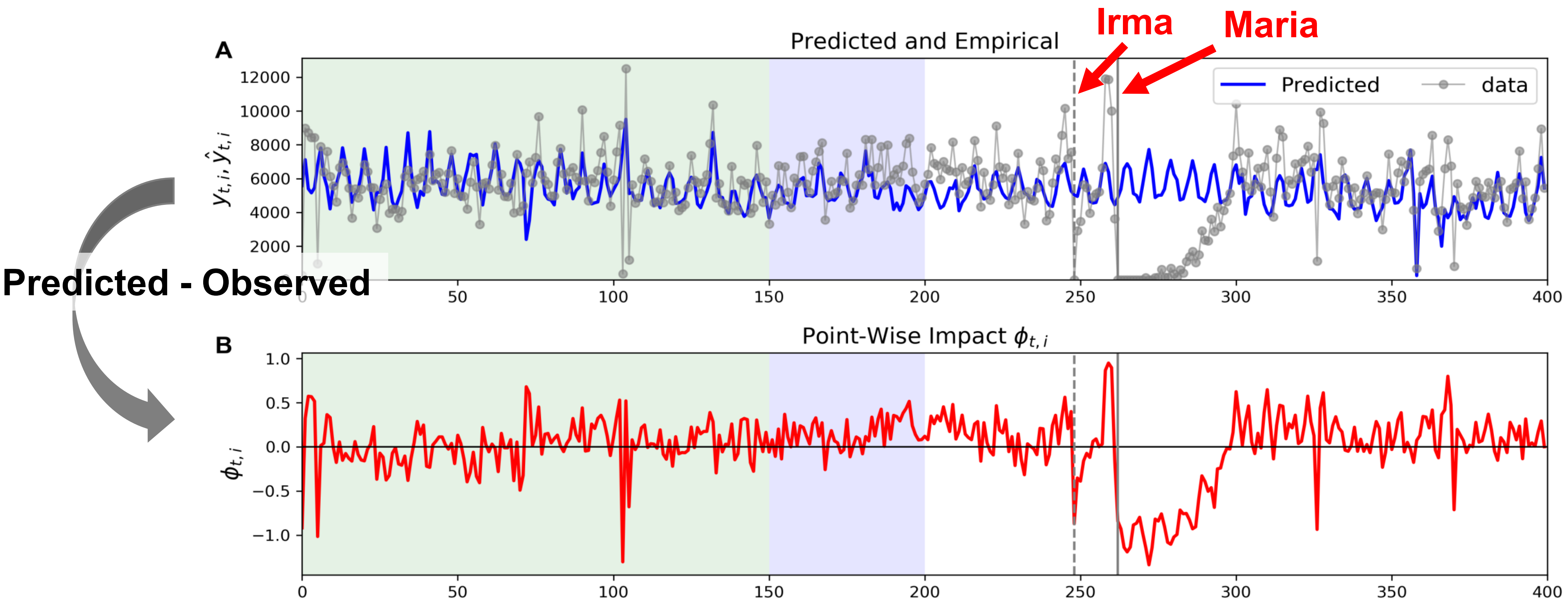

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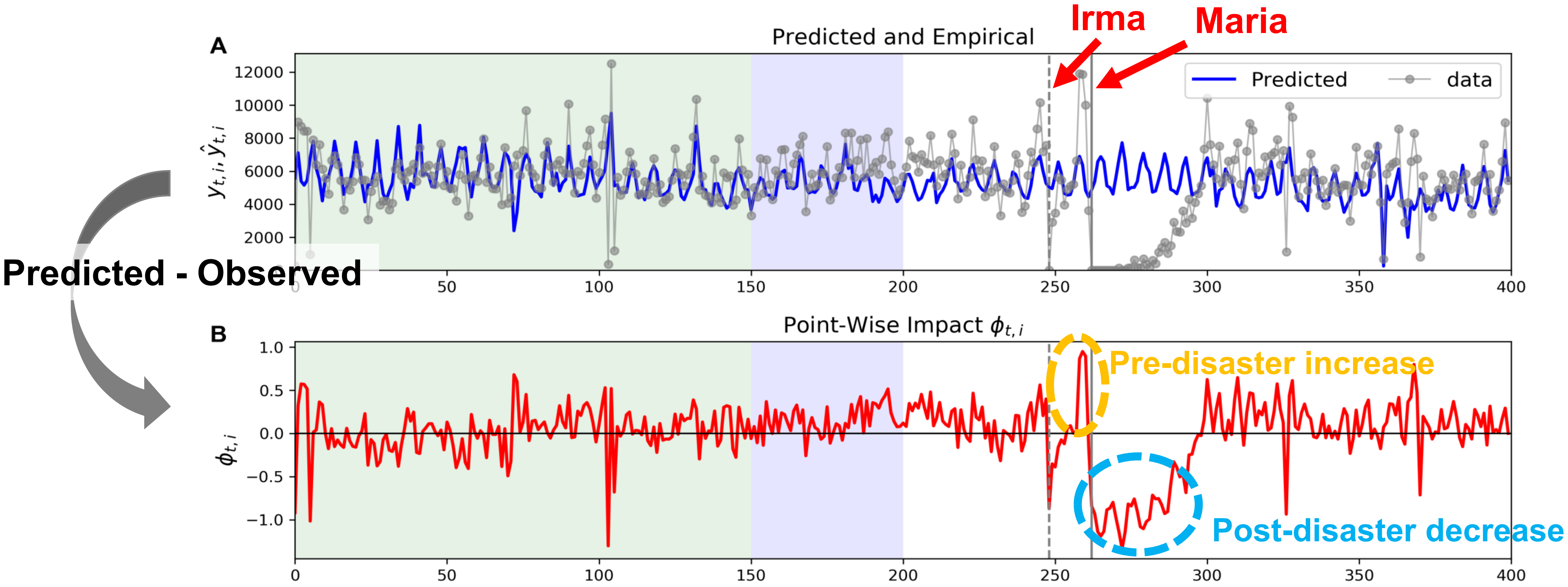

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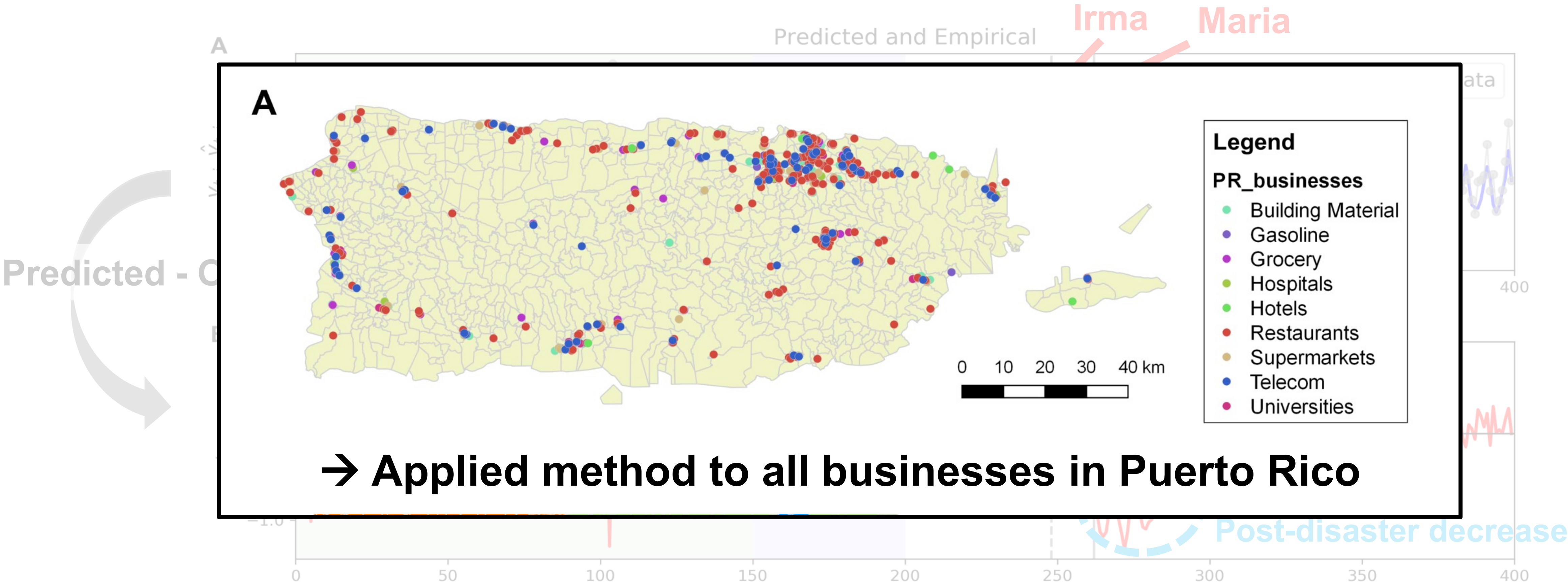


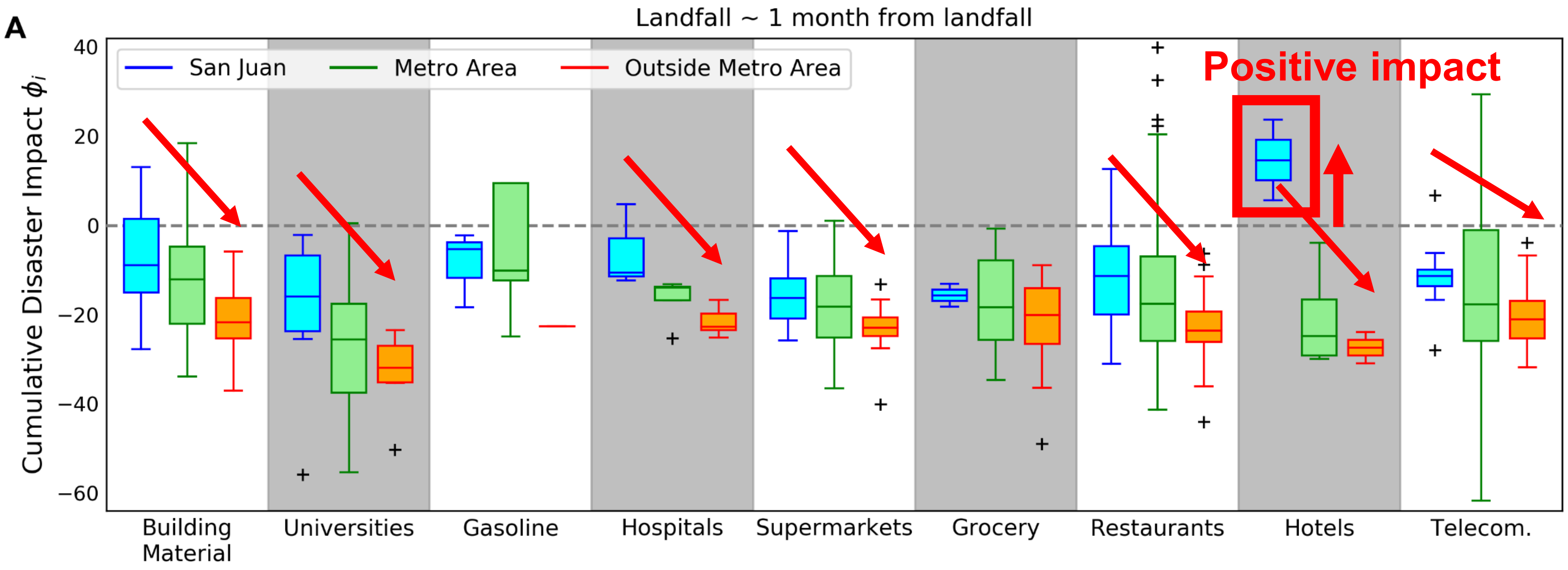
→ **Applied method to all businesses in Puerto Rico**

Quantifying the Economic Impact of Extreme Shocks on Businesses using Human Mobility Data: a Bayesian Causal Inference Approach. Yabe et al. (2020) https://arxiv.org/abs/2004.11121

Disaster impact by category and location

- Cumulative disaster impacts were more severe in rural areas.
- Impacts differed across business categories (gasoline stations ↔ universities)

→ **We can use these estimates to quantify the $$$ loss from mobility data!**



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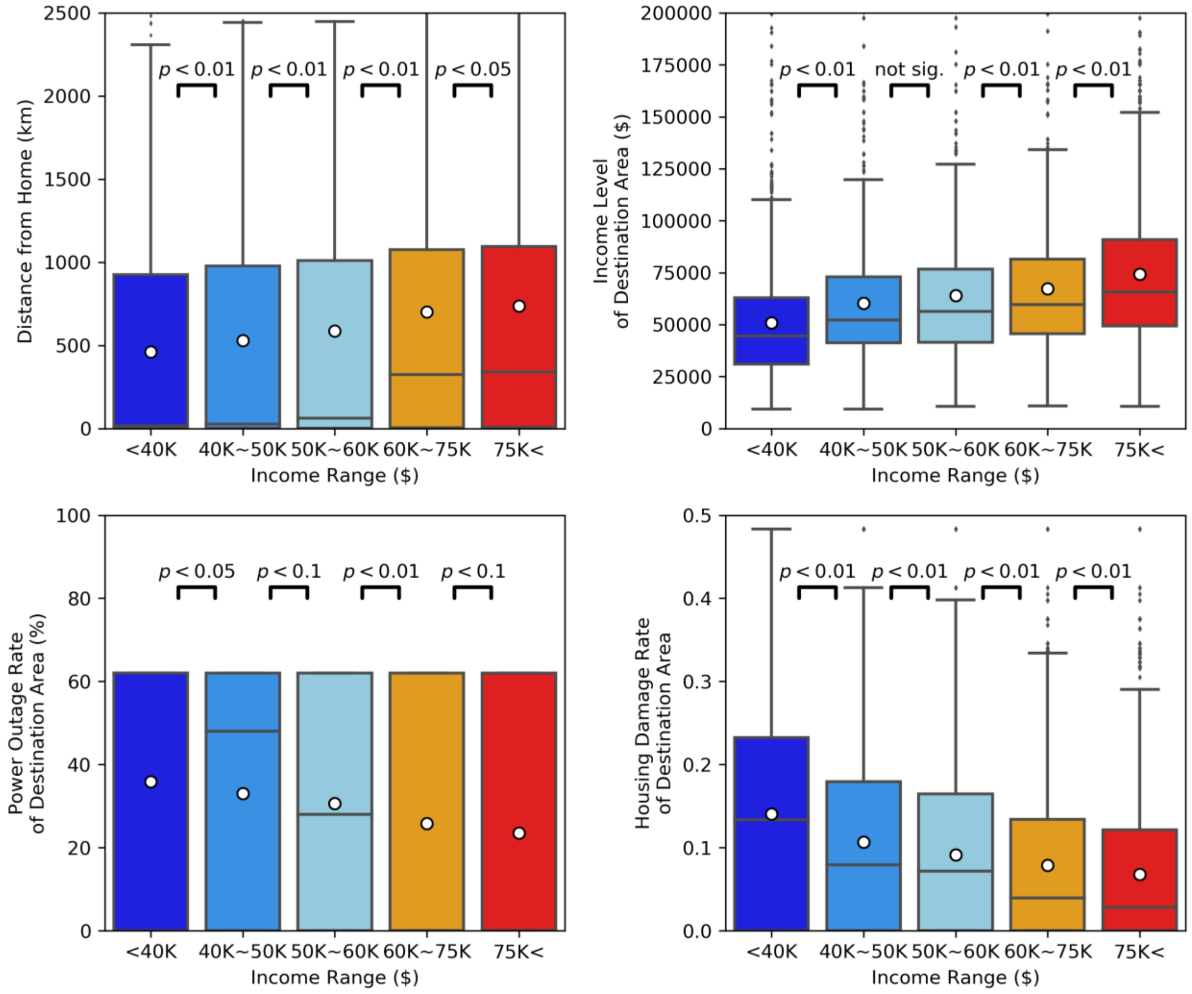
Mobility Patterns reveals Inequality in post-disaster Recovery

Intra-regional inequity in evacuation destinations

- Characteristics of evacuation destinations after Irma.
- High income populations were able to reach places with:
  - Longer distance from Miami
  - Higher income levels (richer neighborhoods)
  - Areas with less power outage rates
  - Areas with less housing damage rates.



Effects of income inequality on evacuation, reentry and segregation after disasters. Yabe & Ukkusuri. (2020). ***Transportation Research Part D: Transport and Environment, 102260***

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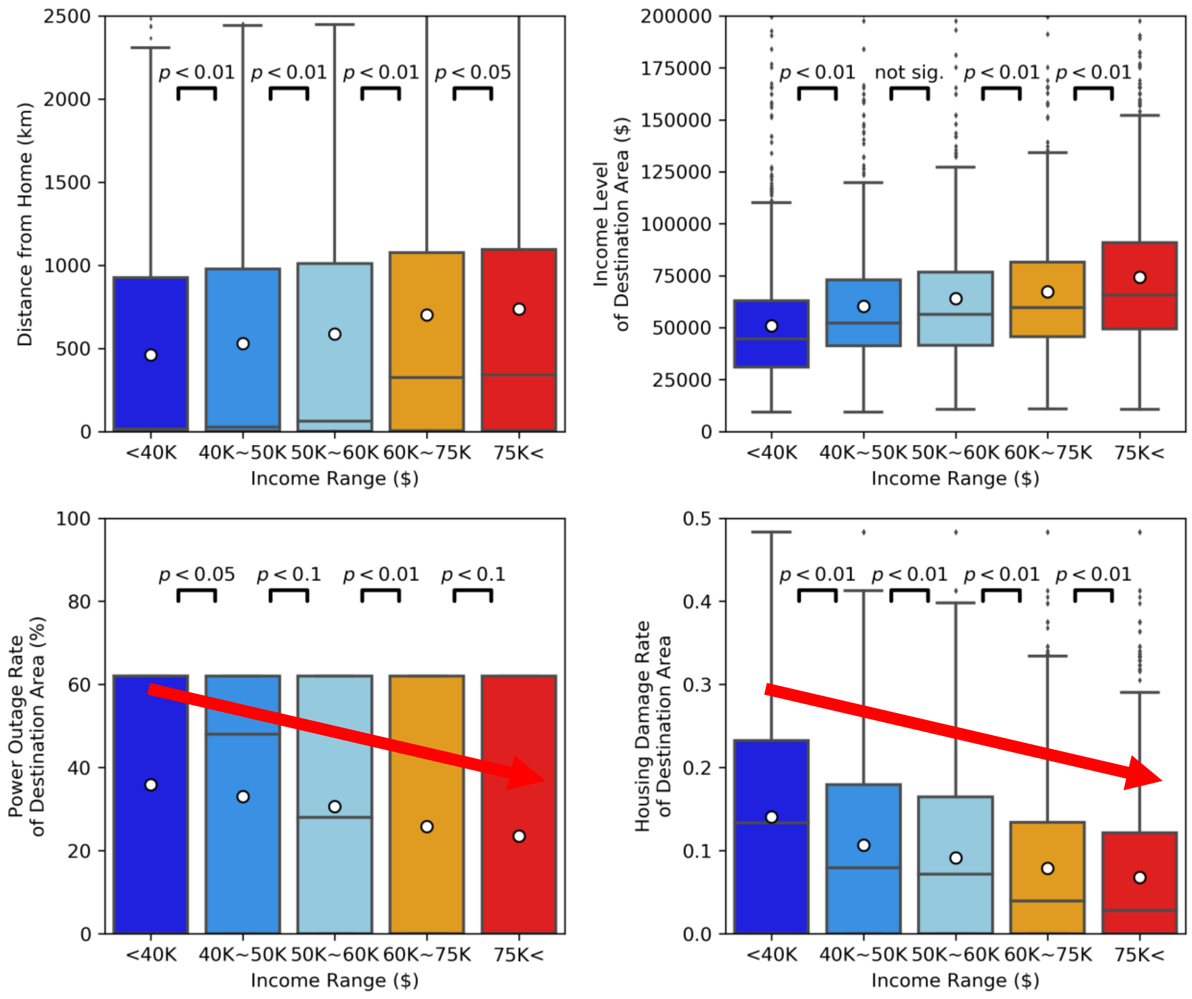


Effects of income inequality on evacuation, reentry and segregation after disasters. Yabe & Ukkusuri. (2020). ***Transportation Research Part D: Transport and Environment, 102260***

Can we model these recovery patterns observed from mobility data?

Modeling recovery of socio-physical systems

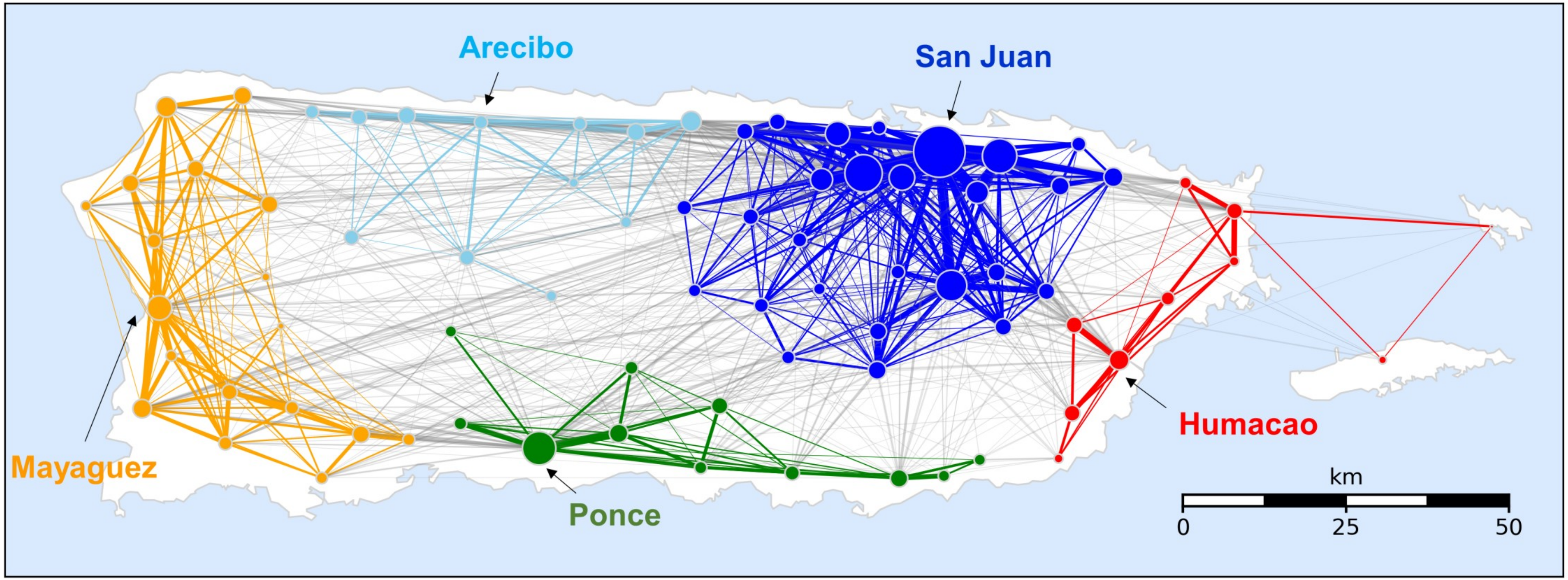
Questions:

- Can we model the recovery of social and physical systems after disasters?
  - Are there interdependencies between these two systems?
  - How do the dynamics differ across communities and industries?
    - What characteristics explain such spatial heterogeneity?

Approach:

- Calibrate a conceptual model of socio-physical dynamics using past data.
- Input: shock profiles of disasters, epidemics etc.
- Output: recovery trajectories of social and physical systems.

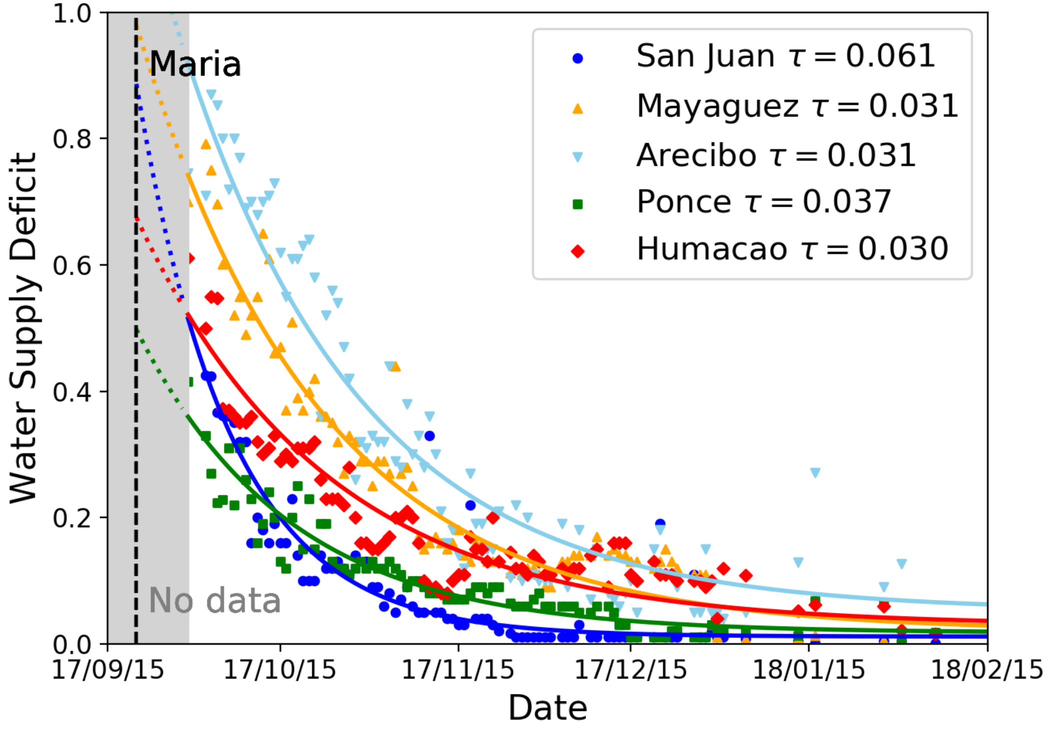
Case study of regional recovery in Puerto Rico after Hurricane Maria (2017)



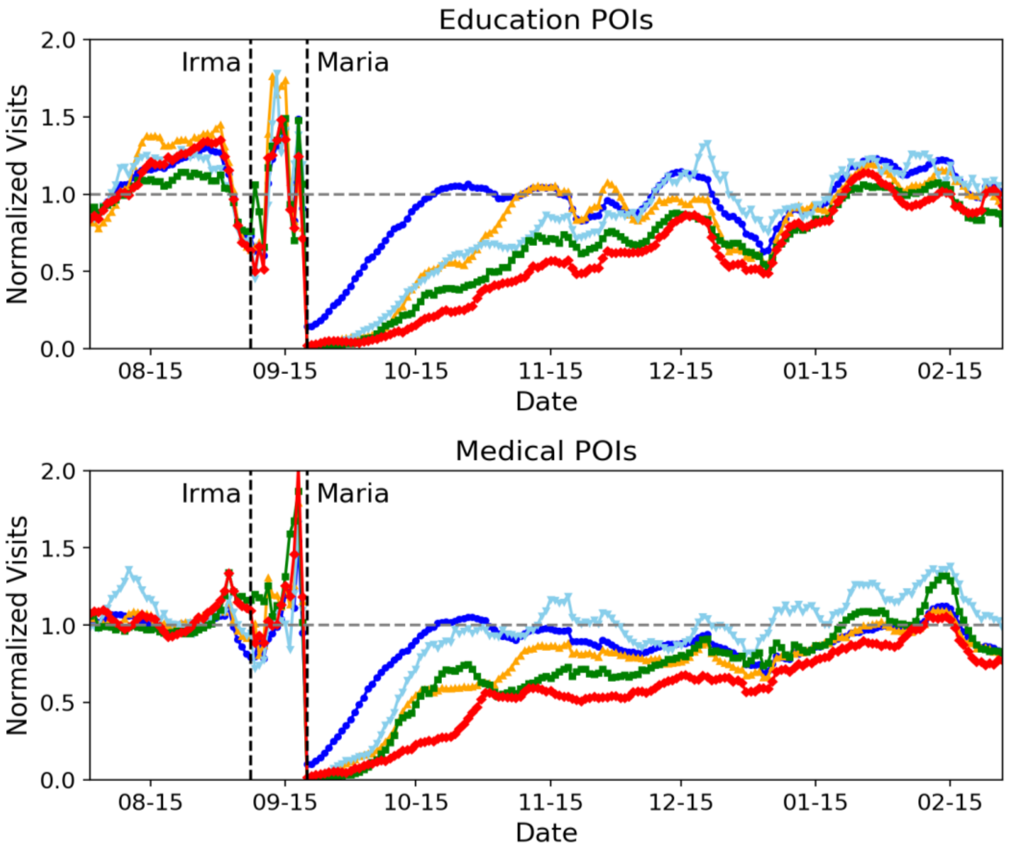
Data-driven Inference of Interdependent Dynamics between Social and Physical Systems during Disaster Recovery. Yabe, Rao & Ukkusuri. *(in preparation)*

Data we used to fit the model

- Recovery of water service deficit



- Recovery of social infrastructure



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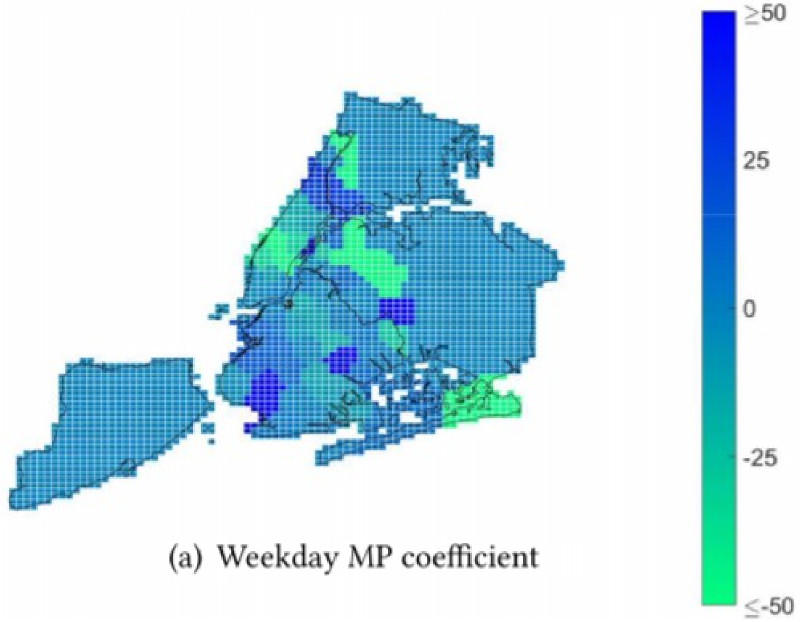
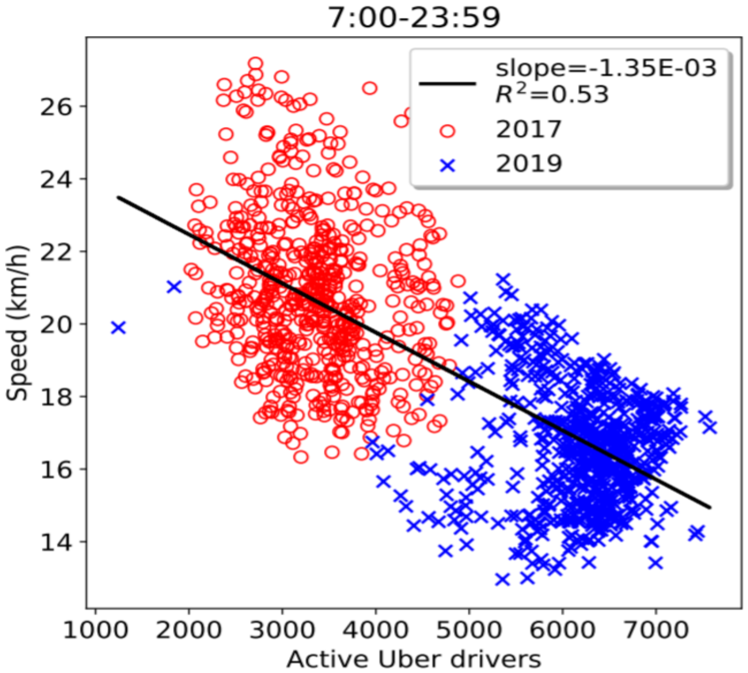
Works on smart mobility and ridesharing





Significant spatial heterogeneity in search time

More Uber drivers → more congestion

Understanding the operational dynamics of Mobility Service Providers: A case of Uber. Qian et al. (2020) ***ACM Transactions on Spatial Algorithms and Systems***

Impact of transportation network companies on urban congestion: Evidence from large-scale trajectory data. Qian et al. (2020) ***Sustainable Cities and Society***

Summary

- High Resolution Mobility Data provide answers to important questions in Cities:
  - Spatio-temporal patterns
  - Economic impacts (measured by foot traffic)
  - Recovery of communities
  - Covid-19 social distancing metrics
  - Inequalities in community recovery
  - Sustainability Impacts
- Way Forward: Work with ADBI
  - Covid-19 Impacts using mobility data
  - Estimate economic impacts using mobility data after disasters and Covid-19 type of shocks
  - Uber, Lyft, and Emerging Mobility Impacts on Cities – e.g. Emissions and Sustainability

We look forward to continuing our work with ADBI on topics of societal relevance!

Acknowledgements

- NSF CRISP and Hazards SEES Project
- PhD Candidate, Takahiro Yabe
- Dr. Xinwu Qian
- Prof. Suresh Rao